Catena 163 (2018) 42–53

Contents lists available at ScienceDirect

Catena

journal homepage: www.elsevier.com/locate/catena

# Adjustment of a weather generator to represent actual rain erosivity in the northern Black Forest – Germany

J. Haas*, H. Schack-Kirchner, F. Lang

*Soil Ecology, Institute of Forest Sciences, Albert-Ludwigs-Universität Freiburg, Germany*

ARTICLE INFO

*Keywords:*
Climate change
Soil erosion
WEPP
Kinetic energy function
R-factor

ABSTRACT

To estimate the impact of highly erosive precipitation on existing and planned forest infrastructure we deem the Forest Service WEPP Interfaces, based on the Water Erosion Prediction Project (WEPP), feasible.

As a first step towards testing WEPP and especially the implemented weather generator CLIGEN for conditions in Germany we evaluated the application of CLIGEN to calculate rain erosivities from generated time series. CLIGEN parameters were taken from time series of up to 17 years with 10-minute resolution from three sites in the Northern Black Forest, southwestern Germany. We assessed a rain kinetic energy function for this region from field measurements with a laser disdrometer to compare CLIGEN performance using the local function to using common kinetic energy functions.

We showed that running CLIGEN with unaltered input parameters is not suitable to model climatic conditions and erosivity indices in the Northern Black Forest. R-factors from unaltered model runs deviated extremely from observed R-factors, resulting in just one third of observed values. Model performance and parameter uncertainties do not benefit much from the use of a site specific kinetic energy function. Differences in model errors and sensitivities compared to a well-established kinetic energy function remain negligible. However, model output was improved by empirical calibration of input data. Virtual best parameter sets for best model results could be identified.

To reproduce observed rain erosivities the input parameters of CLIGEN have to be manipulated to model a precipitation regime where daily precipitation amounts and maximum precipitation intensities are higher at a lower number of rainy days.

We also identified the input parameters to which the model is most sensitive to when manipulated, i.e. precipitation amount and frequency, and maximum peak precipitation. These parameters are especially important when implementing future climate change scenarios.

## 1. Introduction

Soil erosion in forest ecosystems is a problem rarely discussed in European Forestry (Borelli et al., 2016). It is assumed that stable forest ecosystems are not prone to soil loss. Also rain erosivities are low and practices promoting erosion like clear cuttings are rare. However, studies from North America under soil, vegetation and management conditions comparable to Western and Central Europe have shown that up to 90% of sediment delivered from forested watersheds derive from logging infrastructure (Grace III, 2003).

Under the perspective of a changing global climate an increase in extreme weather phenomena is expected. For instance, in Southwestern Germany the occurrence of heavy rain storm events in the winter half-year where logging operations usually take place increased by 5% to 40% in the period from 1931 to 2005 (KLIWA, 2008). To estimate the impact of highly erosive precipitation on existing and planned forest infrastructure several equations and models are available.

As an approach to forest related erosion scenarios we deem the Forest Service WEPP Interfaces (Elliot et al., 2000) most feasible. The interfaces are based on the Water Erosion Prediction Project (WEPP, Flanagan and Nearing, 1995), developed in the United States, and facilitate the application of WEPP to forest specific problems like erosion from forest roads or disturbed forests. Forest practices and soil properties in North America can be considered at least in parts comparable to those in Central Europe. Hence it would be desirable to make the FS WEPP technology available to forest specialists here.

To provide WEPP with the necessary climate input data the model is shipped with the built-in stochastic weather generator CLIGEN (Nicks et al., 1995). CLIGEN produces time series of daily values of precipitation patterns, temperature, radiation, wind, and dew point

* Corresponding author.
*E-mail address:* Julian.Haas@bodenkunde.uni-freiburg.de (J. Haas).

https://doi.org/10.1016/j.catena.2017.12.006
Received 19 December 2016; Received in revised form 8 November 2017; Accepted 6 December 2017
Available online 13 December 2017
0341-8162/ © 2017 Elsevier B.V. All rights reserved.

temperature. The weather generator can be driven with climate files containing parameters which all but one describe the annual distribution of that parameter on a monthly basis. Future climate scenarios and their impact on soil erosion only evolve to their full potential after a certain period. It is necessary to have a model that can supply weather data of desired length, e.g. several decades or centuries, of which CLIGEN is capable.

While the WEPP model has experienced global acceptance and was subject to many studies CLIGEN has been tested only in few applications outside of the US. Among those are studies from Australia (Yu and Rosewell, 2001; Yu et al., 2000), Brazil (Favis-Mortlock and Guerra, 1999; De Maria et al., 2001), the UK (Favis-Mortlock, 1994; Brazier et al., 2001), Korea (Kim et al., 2009), and Taiwan (Fan et al., 2013). Even if these studies consider local CLIGEN performance as sufficient, we were not satisfied with our findings when beginning the work for this study and those of other studies from Germany (Al-Mukhtar et al., 2014).

Three basic assumptions underlay CLIGEN: (1) on a day where precipitation occurs there is only one storm with a maximum duration of 24 h, (2) this storm has a single peak pattern, and (3) the storm can be described by a double exponential function. This simplified representation of internal storm patterns is a limitation to CLIGEN. Storms generated by CLIGEN are described by 4 daily parameters: precipitation amount, storm duration, peak intensity and the time to peak intensity. WEPP uses these 4 parameters to disaggregate storms into more complex patterns via a double exponential function. For single day events with one single peak this representation may be sufficient. But the complexity of events with multiple peaks or durations > 24 h is underrepresented. Climatic regions like the Black Forest have a certain percentage of relatively uniform and extensive precipitation events, in some cases lasting over more than one week. Due to large cumulated precipitation quantities and temporary saturation of soil pores (Morgan, 2005) these events might still generate surface runoff and become erosive. For those situations the simplified representation in CLIGEN might not suffice.

Yu (2002) presented a method focusing on modeling daily rain erosivity expressed as $EI_{30}$-values of the Revised Universal Soil Loss Equation (RUSLE, Renard et al., 1997) from daily CLIGEN precipitation output. The author derives a double exponential function for each day by using the generated parameters for precipitation amount, duration of a storm, peak intensity and the time from the beginning of a storm to its peak. This double exponential function is identical to the one used in the WEPP model itself to depict daily rainfall patterns. $EI_{30}$-values are then calculated by integrating the unit energy function from RUSLE over the double exponential storm pattern. In this study we apply this method as a first step towards evaluation of CLIGEN performance for the Northern Black Forest, possibly making CLIGEN and hence FS WEPP available in the future to application in this region. Furthermore, $EI_{30}$-values can form the basis to RUSLE itself, a model which also might produce satisfactory results for easy assessable topographic conditions like forest roads. Maps of $EI_{30}$-values, or the closely related R-factor, are readily available in Germany (Sauerborn, 1994). According to those maps erosivity in Germany, expressed as RUSLE R-factor, rarely exceeds 1500 MJ mm $ha^{-1}$ $h^{-1}$ $yr^{-1}$ and is usually well below (compare Fig. 1). These comparably low values are a consequence of rather low precipitation intensities in extensive rain events with low mean precipitation intensities, which are typical for the climate. Arguably the R-factor might be unsuitable for those climatic conditions and there is doubt if functions from (R)USLE established in the United States are valid for climatic conditions at differing locales (Kinnell, 1980; McIsaac, 1990). For example antecedent soil moisture indices might locally be better predictors to describe imminent soil erosion events. Still, in this study we decided to include $EI_{30}$ in our method for two major reasons: Firstly, this erosivity index is, despite its possible limitations, widely accepted by public authorities and professionals in Germany as a tool to assess erosion risks in agriculture, and is taught in both academic and job training contexts. To further address those doubts we want to evaluate, if a local function for the Black Forest is needed. Secondly, the index is mathematically well defined and hence a sound target function for comparison and benchmarking of the performance of a weather generator.

The main focus of this study is to present a framework to evaluate the potential of CLIGEN application as part of erosion prediction concepts in Central Europe with the help of the method proposed by Yu (2002). In this we attempt to clarify the following questions:

1. Is CLIGEN suitable to model climatic conditions and erosivity indices in the Northern Black Forest?
2. Is it necessary to find and apply a local rain kinetic energy function instead of standard functions from differing climates, and does this improve the method of Yu (2002)?
3. How sensitive is each input parameter to empirical manipulation and how do sensitivities affect e.g. implementation of future climates?
4. Can model output be improved by limited empirical manipulation of input data?

In this study we addressed the suitability of CLIGEN to model climatic conditions and erosivity indices in the Northern Black Forest by applying the method proposed by Yu (2002) to data from 3 sites in the region. Then we compared model output to erosivity indices directly derived from pluviograph data. To evaluate the necessity and possible benefits of a local rain kinetic energy function the indices were calculated using common kinetic energy functions and a local function which was established from rain kinetic energy measurements from a field campaign. To evaluate the sensitivities of CLIGEN input parameters the parameter sets of the 3 sites were stochastically varied and the output of model runs driven by the derived parameter sets were benchmarked against observations with two goodness of fit (GOF) parameters. To address the question if model output can be improved by empirical manipulation only those model runs were evaluated where modeled mean annual precipitation did not pass a threshold of 5% deviation from observed annual precipitation. From these runs sets of virtual best parameters were established which might be used as a workaround to obtain better estimates of erosivity using CLIGEN.

## 2. CLIGEN functionality and history

The development of CLIGEN is rooted in weather generators used in the EPIC (Erosion-Productivity Impact Calculator, Williams et al., 1984) and SWRRB (Simulator for Water Resources in Rural Basins, Arnold et al., 1990) models. The model version used in this study is CLIGEN v5.3 (Meyer et al., 2002; Zhang and Garbrecht, 2003; Meyer et al., 2008). The algorithms used in CLIGEN are provided in great detail in the aforementioned studies and the documentation of older model versions (Nicks et al., 1995).

Rain-related input parameters to CLIGEN are provided in a parameter file which consists of monthly values for mean, standard deviation and skewness coefficient of rain amount on a day where precipitation occurs, the monthly mean maximum 30-minute rainfall intensity, and the probabilities of a wet day following a wet day and a wet day following a dry day. Also represented by 12 values is an empirical cumulative distribution of the time to peak ratio, i.e. CLIGEN assumes that time to peak does not vary seasonally and so the distribution applies to the entire year.

Precipitation occurrence is modeled based on a first-order, two-state Markov chain. The conditional probabilities of a wet day following a wet day $P(W|W)$ and a wet day following a dry day $P(W|D)$ define the probability of a day where precipitation occurs $P(W)$. For a time series of desired length CLIGEN generates 4 daily precipitation variables: precipitation depth $P$ in mm, duration of a rain event $D$ in hours, peak storm intensity $i_p$, and the time from the beginning of the storm to its

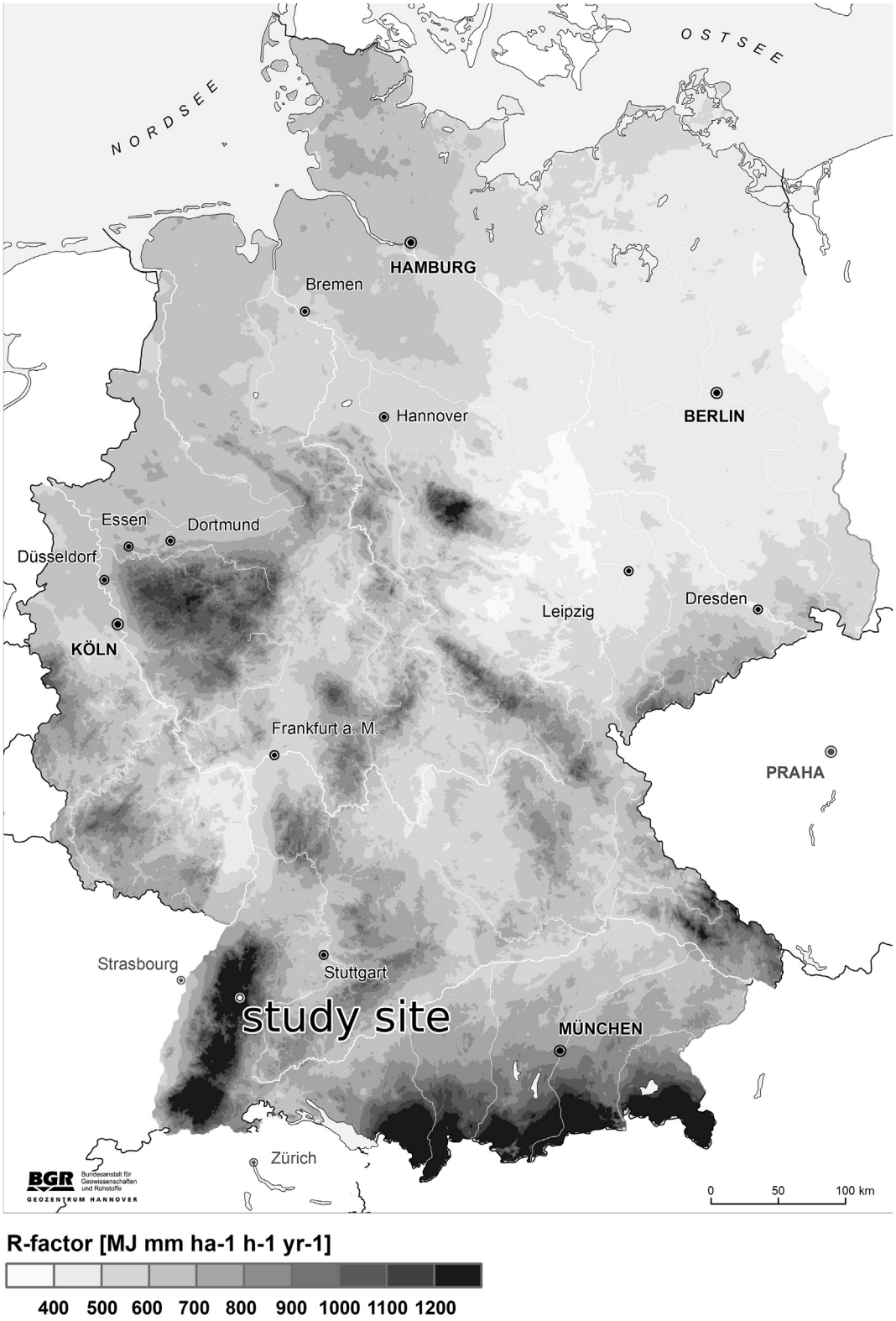


**Fig. 1.** Map of rain erosivity in Germany (Kruse, 2016). The study site in the Northern Black Forest is located in one of the areas with highest rain erosivities.

peak intensity $t_p$. If precipitation occurs $P$ is drawn from a skewed normal distribution defined by mean, standard deviation and skewness (Nicks and Lane, 1989). $D$ is generated by the same method as used in SWRRB (Arnold et al., 1990), and $i_p$ is generated by a method proposed by Arnold and Williams (1989), both based on a gamma distribution of the mean maximum 30-minute rainfall intensity. Time to peak intensity $t_p$ is drawn by sampling the cumulative frequency distribution with a uniform random deviate between 0.0 and 1.0. $i_p$ is normalized by the average storm intensity $P/D$ and $t_p$ is normalized by storm duration $D$, so both variables are dimensionless. If no precipitation occurs all those variables are 0.

To obtain an "actual" rain WEPP disaggregates these 4 variables by a double exponential function into a storm intensity pattern. WEPP then uses this pattern to drive the Green-Ampt Mein-Larson (GAML)

infiltration model (Mein and Larson, 1973; Chu, 1978; Stone et al., 1995). The double exponential function is:

$$i(t) = \begin{cases} i_p e^{b(t-t_p)} & 0 < t < t_p \\ i_p e^{-bt_p(t-t_p)/(1-t_p)} & t_p < t < 1 \end{cases} \quad (1)$$

where $b$ is implicitly dependent on $i_p$ and $t_p$:

$$i_p(1 - e^{bt_p}) - bt_p = 0 \quad (2)$$

and $i_p$ is normalized peak intensity, and $t_p$ is normalized time to peak intensity, both dimensionless. One major consequence to this is a simplified representation of internal intensity patterns. For example, multiple peaks or breaks during precipitation events are suppressed. The simplification to one daily event and its impact on infiltration (Nicks et al., 1995), pauses between two periods of rain (Stone et al., 1995) or antecedent moisture content (Savabi and Williams, 1995) was already discussed. The effect of a precipitation regime with events lasting over more than a week with multiple peaks is less elaborated until now.

It is evident that predicted runoff and soil loss is most sensitive to the four daily precipitation variables (Nearing et al., 1990; Chaves and Nearing, 1991) and are hence most important when implementing future precipitation scenarios. Several studies suggested to implement future changes by simply increasing CLIGEN output of daily precipitation by a certain proportion (Favis-Mortlock and Boardman, 1995; Favis-Mortlock and Savabi, 1996; Favis-Mortlock and Guerra, 1999). Pruski and Nearing (2002) discuss the modification of CLIGEN input parameters and consider changes to be made to precipitation amount and precipitation occurrence frequency to a similar extent. Yu (2005) tested various approaches to implement future precipitation scenarios. He found out that proportional changes of CLIGEN output lead to maximum impacts on WEPP output bearing the risk of overestimation of soil loss. In contrast to that the sole modification of precipitation amount and occurrence frequency input parameters leads to considerable underestimation of soil loss. He concludes that a simultaneous adjustment of all precipitation parameters is needed for generation of precipitation change scenarios. This study from Australia furthermore showed that most of the increase in rainfall in historical recordings is a result of the increase in wet day precipitation depth with high standard deviation. Also both wet-following-wet transition probability and maximum 30-minute rainfall intensity are positively correlated with the change in precipitation depth. Overall the sensitivity and importance of adjustment of CLIGEN input parameters to implement site specific future climates remain less evaluated in literature.

## 3. Material and methods

### 3.1. Study site and data

The study site is located within the municipalities of Baiersbronn and Freudenstadt in the northern part of the Black Forest in southwestern Germany (Fig. 1). The Black Forest lies between 200 and about 1500 m ASL. The region around the study site is mainly covered by replanted long-rotation spruce stands on cambisols with Bunter sandstone below (Gauer and Aldinger, 2005). The area has an Atlantic climate with annual precipitation locally exceeding 2000 mm (Gauer and Aldinger, 2005). Hence the study site represents an area where highest rain erosivities in Germany apart from the Alps occur. Expressed in R-factors from the Universal Soil Loss Equation (USLE, Wischmeier and Smith, 1978) erosivity goes beyond 1500 MJ ha mm $h^{-1}$ (Sauerborn, 1994, compare Fig. 1).

Courtesy of Deutscher Wetterdienst (DWD, German Meteorological Service) weather data from 3 stations were obtained: Baiersbronn-Obertal (DWD station ID: 02752, 622 m ASL, in the following referred to as site A), Baiersbronn-Mitteltal (Q522, 596 m ASL, site B) and Freudenstadt WEWA (02751, 797 m ASL, site C). The stations form an approximately straight line oriented from NE to SW and extending 8 km across the valley of the river Murg. The data sets contained precipitation, temperature and wind speed and direction data in a temporal resolution of 10 min. Data set length without major gaps at site A was 12 years from 1998 to 2009, at site B 6 years from 2007 to 2012 and at site C 17 years from 1996 to 2012, resulting in a total length of almost 2,000,000 entries. In those periods site A experienced a mean annual precipitation of 2041.1 mm, site B 1688.0 mm, and site C 1525.9 mm. Longterm mean precipitation derived from daily DWD measurements in 1981–2010 at site B is 1787 mm and at site C 1575 mm, hence we assume the periods to be representative. While the length of the records might be considered short for CLIGEN parameter generation we want to point out that data with a resolution that high is extremely limited, especially in areas of Germany where forest erosion is an issue at all, considering both published R-factors (Sauerborn, 1994) and topography.

### 3.2. Rain kinetic energy functions

Rain erosivity indices like $EI_{30}$ and the USLE R-factor (Wischmeier and Smith, 1978) are based on the maximum 30-minute intensity $I_{30}$ (mm $h^{-1}$) and the total kinetic energy content $E$ (MJ $ha^{-1}$) of an event, derived from the unit energy content $E_k$ (MJ $ha^{-1}$ $mm^{-1}$) and precipitation amount $P$ (mm). The R-factor is defined as the mean annual sum of $EI_{30}$. While $I_{30}$ and $P$ are standardly available from weather recordings or rather easy to obtain from pluviograph data, determining $E_k$ is not straightforward.

The globally most used transfer functions for $E_k$, describing the relationship between rainfall intensity and kinetic energy, were established on single locations, like Washington, DC (USA), in case of USLE (Wischmeier and Smith, 1978) and Holly Springs, Mississippi (USA), in case of RUSLE (Renard et al., 1997). But due to various site specific factors like altitude, temperature, and air pressure affecting drop size many studies hint to the need of functions from local measurements (Laws and Parsons, 1943; Hinkle et al., 1987). Establishment of such local functions is complicated by a lack in standardized methodology (Kinnell, 1980; McIsaac, 1990) and results vary depending on the time scale of measurements (Panagos et al., 2016).

In agreement to van Dijk et al., 2002 who tested various mathematical representations of $E_k$ (MJ $ha^{-1}$ $mm^{-1}$), we decided on using a continuous, exponential equation as described in Kinnell (1980) and used in RUSLE (Brown and Foster, 1987; Renard et al., 1997). It has the general form of:

$$E_k = e_{max}[1 - a exp(-I/I_0)] \quad (3)$$

where $e_{max}$ (MJ $ha^{-1}$ $mm^{-1}$) is the maximum kinetic energy content, $I$ is rain intensity (mm $h^{-1}$), and both $a$ (−) and $I_0$ (mm $h^{-1}$) are empirical constants. Note that the exponent $-I/I_0$ is often written as $-Ib$ where $I_0$ is $1/b$. The offset $a$ defines the minimum energy content. The factor $I_0$ defines the general form of the resulting curve, where lower values for $I_0$ result in a quicker approach to $e_{max}$.

In the same study van Dijk et al. (2002) reviewed 19 studies from 24 different locations to establish a geographically universal function in form of a continuous, exponential function of the form of Eq. 3. Reviewed studies covered sites in the Americas, Europe, Africa, Asia, Australia and Oceania. The universal function presented is:

$$E_k = 0.283[1 - 0.52\, exp(-0.042I)] \quad (4)$$

with parameters as described in Eq. 3. Note again that Eq. 4 is the original notation of van Dijk et al. (2002). To match the form of Eq. 3 the parameter for $I_0 = -0.042$ has to be written reciprocal as $-1/0.042$. This equation performed well for the sites in Belgium and Italy and not so well in Portugal, thus could be considered a reasonable choice for applications in central Europe.

To establish a local function for the study site, the disdrometer PARSIVEL by PMTech, now produced by OTT Messtechnik Germany, was set up to measure long term rain drop volume and velocity

distributions (Löffler-Mang and Joss, 2000). PARSIVEL is a laser-based optical disdrometer for simultaneous measurement of particle size and velocity of liquid and solid precipitation. Size, hence volume and mass, and velocity determine the kinetic energy of a droplet.

From the data provided by PARSIVEL, mean kinetic energy transported by a number of droplets can be integrated over time and an equation describing the relationship of kinetic energy and rainfall intensity can be established. Due to technical issues with the data loggers only a period of 4 months from May to August 2012 was recorded. Since we had very positive experiences with results from PARSIVEL in former studies (Schmid, 2004) we consider the data obtained reliable. Still, due to the short period any equation derived from these data might be limited in its capabilities to represent kinetic energy contents in a general way. But as highest precipitation intensities occur in the summer months the function derived could still be a valuable orientation and will, alongside a commonly used function, be used in this study to estimate rain erosivity.

### 3.3. Disaggregation of CLIGEN data

(R)USLE and its methods to calculate $I_{30}$ and kinetic energy contents are well established in central Europe and the world and form the basis to our study. Due to the fact that (R)USLE was derived from US data while the universal function proposed by van Dijk et al. (2002) was established considering European data and performed well in describing rain kinetic energy content on European sites, we decided on focusing on the universal function and our local function.

To calculate rain erosion indices from CLIGEN output data we follow a method presented by Yu (2002). By combining Eq. 1 and Eq. 3 total storm energy $E$ (MJ ha$^{-1}$) is calculated as:

$$E = Pe_{max}\left[1 - \frac{ai_p}{B}\frac{I_0}{I_P}\left(exp\left(\frac{-I_P}{I_0}exp(-B)\right) - exp\left(\frac{-I_P}{I_0}\right)\right)\right] \quad (5)$$

again, where $P$ (mm) is precipitation, $e_{max}$ (MJ ha$^{-1}$ mm$^{-1}$) is the maximum kinetic energy content, $a$ defines the minimum energy content, $i_p$ (−) is peak storm intensity, $I_0$ (mm h$^{-1}$) defines the general form of the resulting curve, $I_P$ (mm h$^{-1}$) is re-normalized peak intensity $i_p$, and $B$ (−) is the product of $b$ (−) and $t_p$ (−). This parameter $B$ is more efficiently solved for any given $i_p$ applying Newton-Raphson's method to Eq. 2 (Yu, 2002). The daily storm erosion index $EI_{30}$ (MJ mm ha$^{-1}$ h$^{-1}$) can be calculated as the product of Eq. 5 and the maximum 30-minute rainfall intensity $I_{30}$ (mm h$^{-1}$) given as:

$$I_{30} = \frac{2Pi_p}{B}\left(1 - exp\left(\frac{-B}{2D}\right)\right) \quad (6)$$

for any storm duration $D$ greater 30 min. By definition $I_{30} = 2P$ for any $D$ less than or equal to 30 min. For greater detail on the method refer to Yu (2002).

### 3.4. Aggregation of pluviograph data

To compare $E$, $I_{30}$, and $EI_{30}$ derived from observed 10-minute pluviograph data to those derived from CLIGEN-generated data, pluviograph data were manually aggregated to have the form of CLIGEN model output. This was done by an SAS script we wrote. As common a day was defined as a 24-h period starting and ending at 9.00 AM (Yu, 2005). For each day the CLIGEN parameters $P$, $D$, $i_p$ and $t_p$ were determined. $EI_{30}$ was calculated once with parameters taken from the universal $E_k$-function and once with the local $E_k$-function, using Eqs. 5 and 6. Erosive events taken into consideration for comparison had to have at least 10 mm of precipitation or, if less, a maximum 30-minute intensity of at least 10 mm h$^{-1}$ to prevent overestimation of low intensity rainfall (Wischmeier and Smith, 1978).

### 3.5. Monte-Carlo simulations

CLIGEN input parameter files were prepared for all sites following the procedure described in Yu (2005). Again, a day was defined as a 24-h period starting and ending at 9.00 AM. A wet day was defined as a day where at least 0.2 mm of precipitation occurred. Input file generation was also done with SAS.

In a Monte-Carlo simulation input parameters relevant for precipitation, namely mean precipitation (hereafter abbreviated as *meanp*), standard deviation (*sdevp*), skewness (*skewp*), maximum 30 minute precipitation (*mx5p*), and the two transition probabilities (*pww* and *pwd*), were varied by a factor in pre-defined boundaries: *meanp*, *sdevp*, *pww*, *pwd* and *mx5p* were allowed to obtain a factor of 0 to 4 of its original value, while preventing *pww* and *pwd* from obtaining unnatural probability values of above 1.0. The boundaries of *skewp* were set to a factor of −2 to 4 of its original value, allowing negative values for skewness. In each variation step the same factor was applied to all 12 monthly values of a parameter. The representation of parameters as factors of original values instead of the actually resulting manipulated values was done to keep the different sites with e.g. significantly different annual precipitation comparable. This notation will be used throughout the study. The distribution of time to peak values (*tpk*) was composed with 12 random values. As Freer et al. (1996) suggested for large parameter ranges a high number of Monte-Carlo runs - 50,000 for each site - were performed. Each run generated a CLIGEN time series of 30 years. Model output was bench marked against observations in two ways. Annual distributions of mean monthly $EI_{30}$ sums were compared by calculating the root mean square error (RMSE) between modeled and observed data, making RMSE a measure for overall model performance. Furthermore, each time series of 30 years was collapsed to mean daily $EI_{30}$ values for each Julian day, hence creating artificial years of 366 mean daily $EI_{30}$ values. For performance evaluation of these artificial years the goodness of fit criterion presented by Gupta et al. (2009), here referred to as Kling-Gupta-efficiency (KGE), was used. This criterion expresses model performance at individual days or single extreme values.

To manage the high number of model runs and the resulting output we wrote a Python script. For each Monte-Carlo run the script varied the CLIGEN input parameters in the given constraints, put together a new CLIGEN input parameter file, and called the CLIGEN routine with the new parameters. The script then called an R script which calculated RMSE and KGE values. Parameter sets and goodness of fit parameters were then stored in a MySQL database.

For both goodness of fit criteria the Regional Sensitivity Analysis (RSA) as proposed by Spear and Hornberger (1980) and Hornberger and Spear (1981) and modified by Wagener et al. (2001) was applied. Sensitivity is defined as the effect of a parameter on the model performance represented by those criteria. For every combination of site and kinetic energy function only the best performing 1% in terms of RMSE and KGE respectively were cut off, yielding 12 groups of 500 runs. In those groups likelihood for the according level of performance was calculated. In each group with $n$, here 500, top performing parameter sets likelihood is calculated as:

$$L(\Theta_i) = \frac{1 - C(\Theta_i)}{n - \sum_{i=1}^{n} C(\Theta_i)} \quad (7)$$

with $L(\Theta_i)$ as likelihood of a parameter set $\Theta_i$, $i = 1, \ldots, n$, and $C$ as the criteria value of either RMSE or KGE. Cumulative likelihoods of each group are then plotted against their according variation factor of each parameter of a set. The further a resulting graph deviates from a uniform distribution the more sensitive the model is to variation of that parameter. Also areas in graph with highest slope identify top performing variation factors and parameter values accordingly.

To additionally identify virtual best parameters the 500 top performing model runs were further filtered by adding a threshold of 5%

deviation of modeled mean annual precipitation from observed mean annual precipitation. From the pool of remaining model runs the mean and standard deviation of the determined variation factors were calculated. These means form virtual best parameter sets. The procedure to modify CLIGEN input in order to match a desired output or observation was inspired by the approach used in the FS WEPP interfaces, where existing sets of input parameters are manipulated to meet the user's observations. Further inspiration was drawn from Pruski and Nearing (2002) who adjusted input parameters by certain percentages to evaluate the impact of the changes on WEPP output in the context of climate change scenarios. While it is clear that our manipulated parameters deviate from observed variables and deteriorate observed precipitation patterns to some extent they help understand the unsatisfactory performance of CLIGEN in local climates and how to improve CLIGEN output in terms of $EI_{30}$ values. We do not recommend this approach as standard procedure to parametrize CLIGEN for other geographical contexts. The intent of this final step was to have the generated datasets quickly available to assess the situation at this special site and use them as a workaround to obtain better estimates of erosivity using CLIGEN.

## 4. Results

### 4.1. Rain kinetic energy functions

Two rather commonly established kinetic energy content equations, those from RUSLE and van Dijk et al. (2002), and our locally determined function for the Heselbach catchment, derived from a number of single erosive events, are depicted in Fig. 2. From our measured events two clusters were identified. Corresponding to Blanchard (1953) the linear correlated events, here displayed as round dots, were considered as less erosive drizzle and not included in the following considerations. These events do contribute to total precipitation in a certain way but do not generally accumulate either critical amounts of water to generate surface runoff or critical drop mass to have an impact on particle mobilization. To the remaining events, depicted as triangles, an exponential function of the form of Eq. 3 was fitted, in the following referred to as local function. Compared to the two established functions the local function shows substantially lower values for $E_k$ which result in overall lower kinetic energy contents in precipitation. The local function reaches its relative maximum of kinetic energy content at lower precipitation intensities of around 40 mm $h^{-1}$, while the other functions reach the energy plateau of the graph at around 80 mm $h^{-1}$. The high value of $a = 0.899$ results in low initial energy contents. The low value of $I_0 = 14.52$ causes a rapid rise to maximum kinetic energy contents.

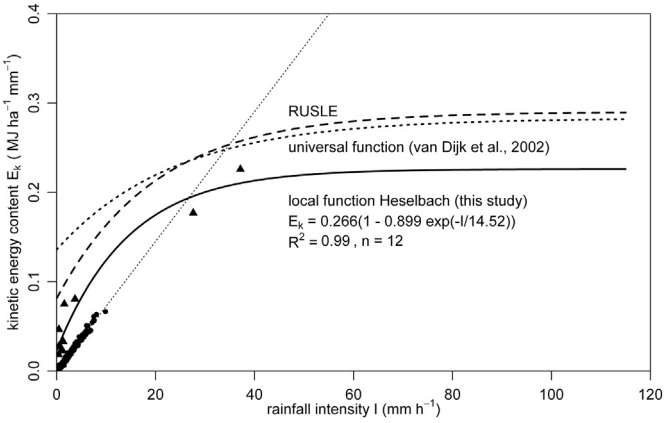


**Fig. 2.** Relationships of rainfall intensity and rain kinetic energy content calculated with equations from RUSLE (Renard et al., 1997) and as proposed in van Dijk et al. (2002). A local function is fitted to data from rain events measured in the Heselbach catchment (triangles). Round dots are considered less erosive drizzle not included in the local function.

### 4.2. Aggregation and disaggregation

Fig. 3 gives an example of a rather typical 6-day event at site C with multiple peaks. The event is displayed as a graph of 10-minute data from a pluviograph and as a graph derived by disaggregation of the four parameters of CLIGEN type data. The dashed lines only symbolize hypothetical peaks if daily CLIGEN type peaks were manually moved to match observed daily maximums of pluviograph data. Note that the hour 0 on the abscissa coincides with 9 AM of a regular day as this is the point in time where a CLIGEN day begins. Days 2 and 3 are exemplary of the before mentioned simplification of daily rain patterns in CLIGEN: in observed data additional smaller peaks of only slightly lower intensities than the largest peak are aggregated to the largest peak in its vicinity. The time period with little or no precipitation is hence overestimated. An example for the opposite situation follows on day 4: in CLIGEN type data only about 2 h pass between the two peaks, whereas the pause in precipitation recorded by the pluviograph was around 9 h.

To compare daily rain erosivities derived from 10-minute pluviograph data with those derived from disaggregated CLIGEN type data, their linear relationships were established for both the universal $E_k$-function and the local $E_k$-function, including data from all sites (Fig. 4).

The linear relationships are $EI_{plu} = 0.867EI_{CLI}$ for the universal function and $EI_{plu} = 0.851EI_{CLI}$ for the local function, where $EI_{plu}$ is daily $EI_{30}$ derived from pluviograph data and $EI_{CLI}$ is daily $EI_{30}$ derived from CLIGEN type data. Both correlate on a high level of 0.922 and 0.897 respectively expressed as $R^2$. Additionally, we calculated the linear relationships of the kinetic energy component $E$ of $EI_{30}$, which are $E_{plu} = 0.978E_{CLI}$ for the universal function and $E_{plu} = 0.936E_{CLI}$ for the local function. The linear relationship between maximum 30-minute rain intensity $I_{30}$ of pluviograph data ($I_{plu}$) and of CLIGEN data ($I_{CLI}$), which is the same for both functions, is $I_{plu} = 0.892I_{CLI}$. The linear relationships should be considered calibration functions to correct biases in $EI_{30}$ calculations from CLIGEN model output at our study sites.

### 4.3. Monte-Carlo simulations

To obtain the error of the best 500 model runs the resulting cumulated sums of mean monthly $EI_{30}$ are plotted together with the cumulative curve of observed mean monthly $EI_{30}$, all calculated with the universal function, each also representing the basis to RMSE calculations (Fig. 5). Also plotted are the model runs with non-manipulated input data, which were the incentive to this study. Note that these cumulated monthly means of $EI_{30}$ differ slightly from R-factors, which are mean annual sums of $EI_{30}$, by roughly + 3%. Also note that these R-factors are substantially higher by a factor of 1.2 to 1.5 than those from Sauerborn (1994) presented in Fig. 1, approximately reflecting the difference between the USLE-function and the universal function. The observed R-factors derived from CLIGEN type data and pluviograph data calculated with both functions as well as the minimum and maximum R-factor of the top 500 model runs from Fig. 5 are summarized in Table 1. Also listed in Table 1 are R-factors from model runs with non-manipulated CLIGEN input data. Here CLIGEN generated R-factors are around 70% lower than observed R-factors. These results are in contrast to those of Yu (2002) where CLIGEN-generated R-factors and *EI*-values of storms with 10-year recurrences are overestimated systematically by around 40% compared to values from the RUSLE database.

The Regional Sensitivity Analysis (RSA) showed that model output was very sensitive to stochastic variation of all rain related input parameters, but the skewness *skewp* (Fig. 6). The *skewp* graphs for all sites with both functions and goodness of fit parameters are almost identical to the 1:1 line. Overall model sensitivity does not differ much when comparing the two kinetic energy functions. The model was slightly more sensitive to variation of *mx5p* when driven with the local

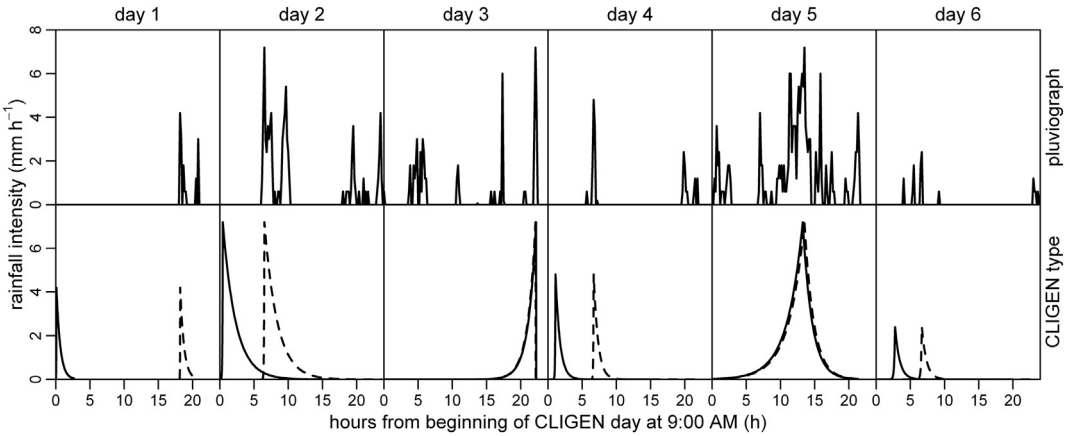


**Fig. 3.** Rain at site C over a period of 6 days as example how storm patterns are simplified in CLIGEN. The upper panels contain graphs drawn along 10-minute pluviograph data. The solid lines in the lower panels depict CLIGEN rain patterns as calculated from the 4 parameters derived from the same data by aggregating observed data manually. To illustrate the potentially wrong representation of periods without precipitation in CLIGEN, the dashed lines are the same CLIGEN patterns shifted to the point where maximum peaks occur in pluviograph data.

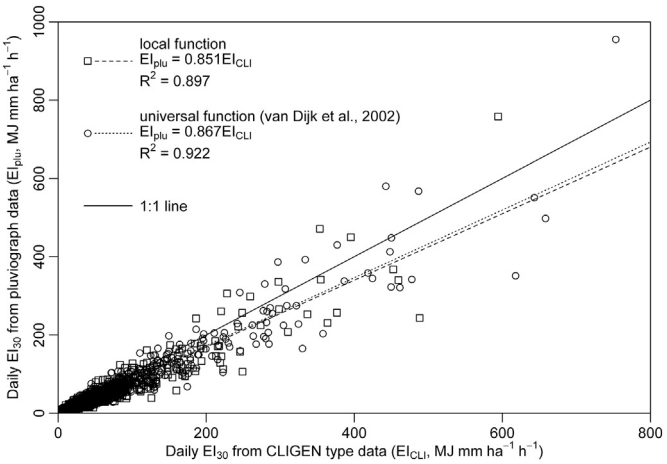
local function
EIplu = 0.851EICLI
R² = 0.897
universal function (van Dijk et al., 2002)
EIplu = 0.867EICLI
R² = 0.922
1:1 line
Daily EI30 from pluviograph data (EIplu, MJ mm ha⁻¹ h⁻¹)
Daily EI30 from CLIGEN type data (EICLI, MJ mm ha⁻¹ h⁻¹)

**Fig. 4.** Relationships between daily $EI_{30}$ derived from 10-minute pluviograph data and from pluviograph data manually aggregated to have the form of CLIGEN model output. Both the universal and the local function were applied. These relationships can be considered conversion functions to compare $EI_{30}$ from CLIGEN output to $EI_{30}$ from pluviograph data.

function and more sensitive to variation of *meanp* when driven with the universal function and focusing on RMSE. Comparing the two goodness of fit parameters the model is generally more sensitive to variation of *meanp*, *sdevp* and *mx5p* when benchmarked against RMSE than against KGE. Also the model is more sensitive at higher variation factors of *meanp* when benchmarked against RMSE than against KGE. Curve forms for the different sites are pretty similar, so model sensitivity is rather homogeneous for all sites. A notable difference occurs at station A (dashed line) for parameters *meanp*, *sdevp* and *mx5p*, where the curve has a slightly higher tendency to the form of the 1:1 line which means a less prominent model sensitivity. The model shows high sensitivity to variation of both parameters describing precipitation occurrence probabilities, *pww* and *pwd*, in a very narrow parameter range.

Since we composed the time to peak distribution, *tpk*, randomly it could not be expressed as factors of their original values and the distribution was aggregated to its median (Fig. 7). The model showed high sensitivities to variation of *tpk* with all combinations of site, goodness of fit parameter and kinetic energy function, all producing virtually identical curves.

After filtering the 500 top performing model runs again by applying the 5% deviation threshold of modeled mean annual precipitation from observed mean annual precipitation only 7 to 57 model runs remained, depending on GOF and kinetic energy function (Table 2). Of these runs the means and standard deviations of the variation factors were calculated.

Focusing on the mean values basically in all combinations of site, kinetic energy function and goodness of fit parameters the model tends to higher values of *meanp*, *sdevp* and *mx5p*. To counter that tendency transition probabilities tend towards factors below 1.0 with only two exceptions (site B, KGE, both functions). This fact results in an overall lower probability that precipitation occurs, $P(W)$, and hence a lower number of wet days. For example, employing the actual parameter values for January from the unaltered parameter file of site A transition probabilities result in $P(W) = 0.87$. After the factors obtained with the

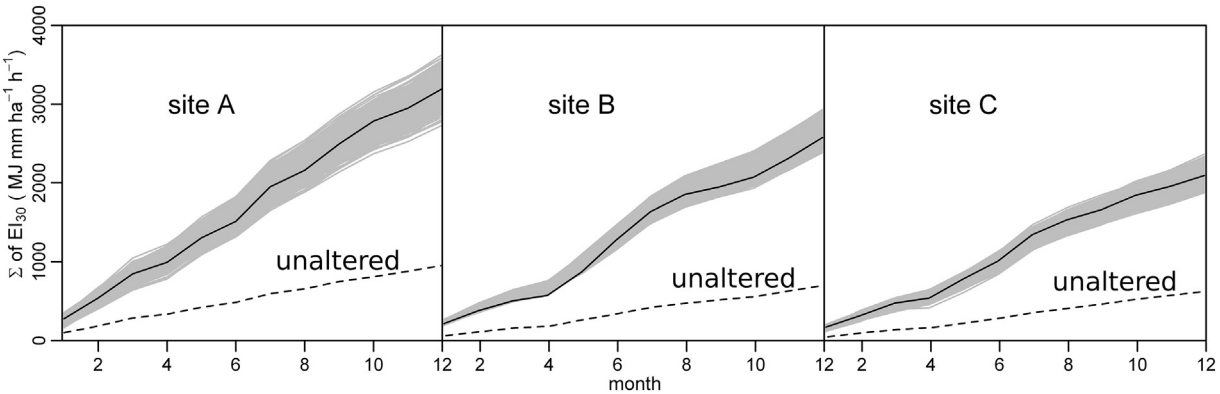


**Fig. 5.** Cumulated sum curves of mean monthly $EI_{30}$ of observed data (black line) and the 500 best performing model runs bench marked with RMSE (gray) at each site. Dashed lines are the curves calculated from model runs with non-manipulated input data (unaltered).

**Table 1**
R-factors (MJ mm $ha^{-1} h^{-1}$) as observed (obs.), as modeled from non-manipulated input data (unaltered) and as minimum and maximum range of 500 best performing model runs from stochastically varied input data. Focus is on CLIGEN type data (CLI) and the universal function, since CLIGEN output was benchmarked with observed data aggregated to the form of CLIGEN output. Results from pluviograph data (PLU) and the local function are given and ratios are valid to convert between data type and functions.

| | | Site A | Quotient to obs. CLI | Site B | Quotient to obs. CLI | Site C | Quotient to obs. CLI |
|---|---|---|---|---|---|---|---|
| Universal function | obs. CLI | 3069.8 | – | 2486.9 | – | 1979.8 | – |
| | obs. PLU | 2702.3 | 0.880 | 2025.4 | 0.814 | 1661.1 | 0.839 |
| | unaltered CLI | 953.0 | 0.310 | 697.9 | 0.281 | 614.4 | 0.310 |
| | unaltered PLU | 838.9 | – | 568.4 | – | 515.5 | – |
| | best 500 CLI min | 2648.1 | 0.863 | 2302.1 | 0.926 | 1771.6 | 0.895 |
| | best 500 CLI max | 3514.3 | 1.145 | 2830.1 | 1.138 | 2235.4 | 1.129 |
| Local function | obs. CLI | 1804.7 | – | 1491.1 | – | 1158.5 | – |
| | obs. PLU | 1546.1 | 0.857 | 1164.5 | 0.781 | 934.4 | 0.807 |
| Universal/local | CLI | 1.701 | – | 1.668 | – | 1.709 | – |
| | PLU | 1.748 | – | 1.739 | – | 1.778 | – |

universal function were applied to the unaltered transition probabilities they result in $P(W) = 0.49$ for RMSE and $P(W) = 0.40$ for KGE.

As already apparent in Fig. 7 the mean and standard deviation values of the median of *tpk* are remarkably homogeneous. Mean values are around or slightly above 0.5. Values close to 0.5 indicate a high symmetry of the disaggregated precipitation patterns.

Mean values in Table 2 can be interpreted as workaround best parameter sets to reproduce observed $EI_{30}$ with CLIGEN at each site, given which GOF is deemed more feasible.

## 5. Discussion

The $E_k$ function we established in our local watershed in the Northern Black Forest is surprising for it's generally lower values for kinetic energy content in comparison to the two common functions. The local function reaches its maximum kinetic energy content at around 50% of the maximum of the other functions. This might be related to our observation that a high fraction of droplets had small diameters resulting in lower masses and, as a consequence, lower kinetic energies. This also correlates with the high amount of drizzle events recorded, which were according to Blanchard (1953) excluded from the fitting of the local function. Excluding those events based on one publication was a difficult choice since the fitting of the local function then had to be made relying on only 12 data points. But note that overall kinetic energy content $E$ would be even lower if the drizzle events were included. Also almost all drizzle events happen below 10 mm $h^{-1}$ intensity. In many cases they would be excluded from $EI_{30}$ calculations due to the premisses for considering an event erosive set by Wischmeier and Smith

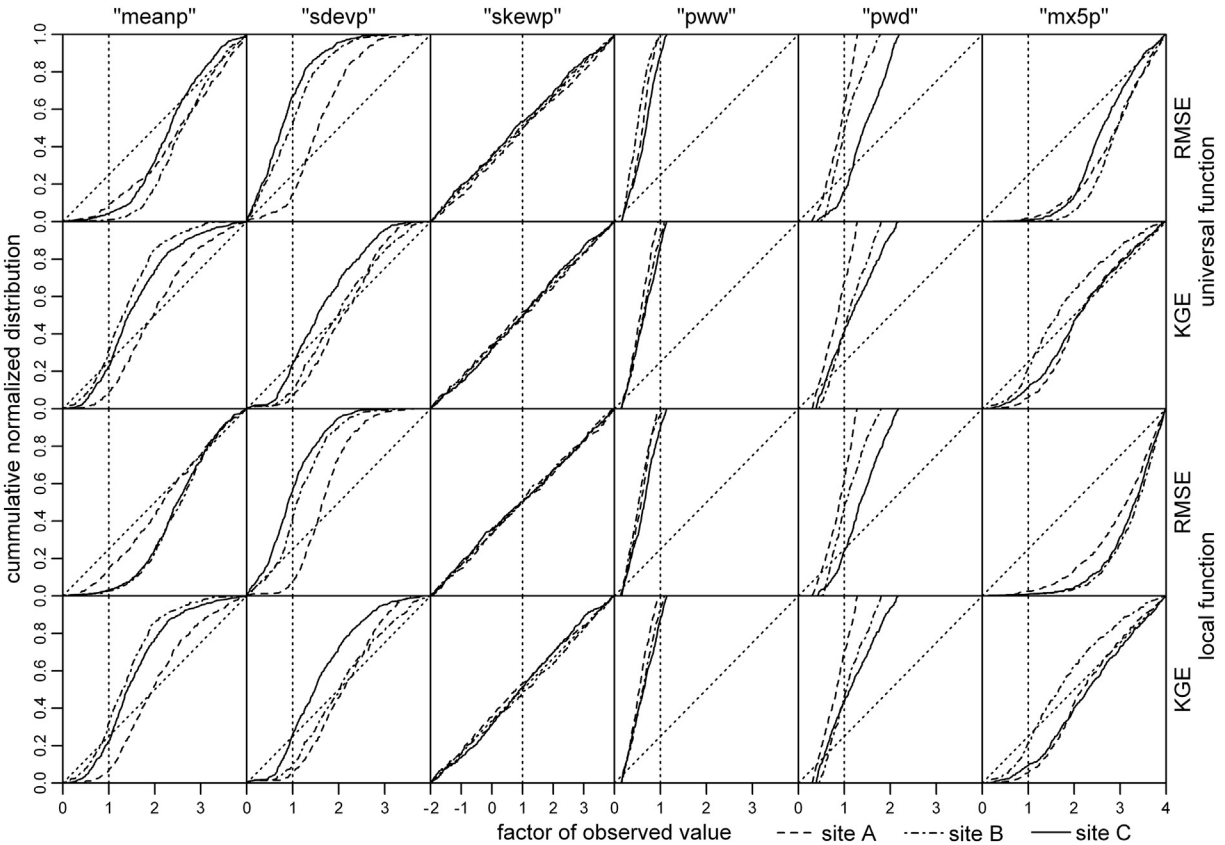


**Fig. 6.** Results of the Regional Sensitivity Analysis (RSA) of 6 model parameters from the 500 best performing model runs. Each curve addresses sensitivity of the model to variation of one parameter at a site derived with one of the two rain kinetic energy functions and bench marked with one of the two goodness of fit parameters. The closer a curve gets to the dashed diagonal 1:1 line, the less sensitive the model is to variation of that parameter. Please note again that the abscissa shows factors applied to the original parameter values to keep the sites comparable. The dashed vertical line is an orientation to where the original observed parameter value is located (factor of observed value = 1).

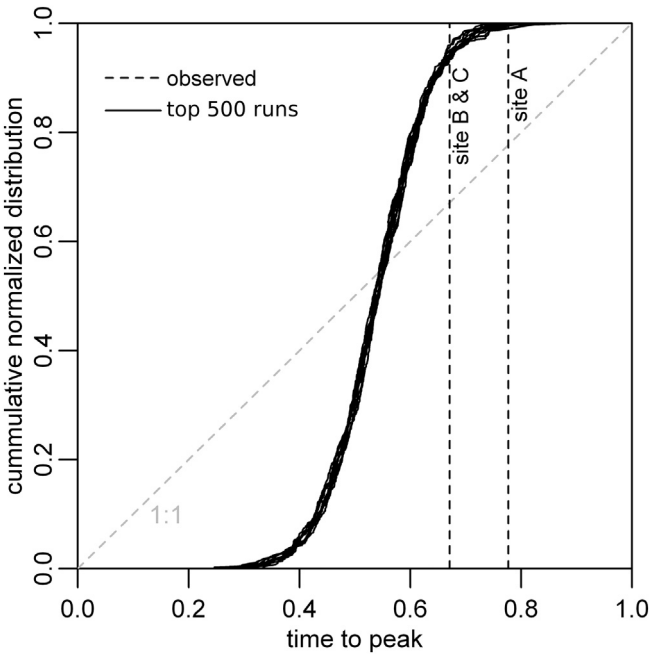


**Fig. 7.** Results of the Regional Sensitivity Analysis (RSA) of the time to peak distribution from the 500 best performing model runs. One curve represents one combination of site, kinetic energy function and goodness of fit parameter. All curves are displayed in one figure and, because of their similarity, form an astonishingly dense set.

(1978).

In calculations of $EI_{30}$ or R-factors the method to derive 30-minute rainfall intensity $I_{30}$ remains the same, no matter which kinetic energy function is used in the further procedure. So the relatively low values for both overall and initial kinetic energy content contribute essentially to lower calculated rain erosivities. This is supported by our findings comparing the different R-factors presented in Table 1. The R-factors calculated with the universal functions are clearly higher than those calculated with the local function by a factor of around 1.7. Even if the two functions run rather parallel to each other for the best part they are the farthest apart below 20 mm $h^{-1}$ and above 60 mm $h^{-1}$. Since intensities of above 60 mm $h^{-1}$ are rare the bulk of this difference presumably originates from events with low rainfall intensities, despite minimum thresholds set by Wischmeier and Smith (1978).

It is difficult to judge how competitive our local function is to the universal function due to the above mentioned circumstances of measurements. But it is evident that deviations of the magnitude found here would impact estimations of sediment production on a significant level. Low observed erosion rates in watersheds of this region might not just be caused by high soil infiltration rates and water storage capacities, as commonly assumed. It is also possible that they are related to actually lower kinetic energy contents than estimated with common functions from other locales. Given this possibility this implies that functions might not be valid unconditionally for other regions and additional measurements of local rain kinetic energy might be feasible.

Leaving it in question how representative a function based on 12 data points is, we will still use the local function to discuss model sensitivities. The main focus in relevant calculations will still remain on the well-tested universal function proposed by van Dijk et al. (2002).

One question we wanted to address in this study is the potential of integrating CLIGEN into less sophisticated erosion prediction concepts using (R)USLE. Since the (R)USLE R-factor is a lumped parameter where preliminary conditions are not considered an advantage of such concepts would be that the limitations of CLIGEN in representing complex rain patterns are of lesser importance. So it is very important to analyze the relationships between $EI_{30}$ or R-factors derived from the simplified CLIGEN patterns and those derived from complex patterns i.e. pluviograph data.

Concerning the relationships we established in this study it is remarkable that even if the universal function performs better in reproducing $E$ than the local function, each method combined with $I_{30}$ results in a rather negligible difference in their deviation from an 1:1 relationship. Furthermore $I_{30}$ seems to have a compensating effect on the deviations. Our results show that in the process of aggregating single rain events to four parameters and disaggregating them again using the WEPP method it happens that rain erosivities are underestimated by around 15% where $I_{30}$ is contributing more to this bias than $E$. This is substantiated by the differences between annual R-factors in Table 1. The high coefficient of determination shows that this deviation is systematic and confirms our assumption, that the relationships can be considered calibration functions to convert between $EI_{30}$ values from CLIGEN type data and pluviograph data.

Before we discuss the results of the sensitivity analyses we want to address the issues of R-factor estimations on which the analyses are based on. R-factors calculated from CLIGEN runs parametrized with the standard procedure, as described in Yu (2005), turned out to be one third of those observed. The top 500 runs with manipulated data performed with a R-factor deviation of < 14.5% from the observed R-factors. Even if R-factor estimation could be significantly improved the manipulation of input parameters to CLIGEN to achieve better output performance is highly problematic. Input parameters are statistical values derived from weather records and should be a fix starting point for model development or improvement. The adjustment factors elaborated in this study should hence only be considered valid for the

**Table 2**
The 500 top performing model runs were again filtered by applying a 5% threshold of deviation of modeled mean annual precipitation from observed mean annual precipitation. Listed here are the means and standard deviations (in parentheses) of the variation factors calculated from the remaining *n* model runs. Please note again: to keep sites comparable the table contains factors applied to the original parameter values and not the resulting manipulated parameter values themselves.

| | Site | n | meanp | sdevp | pww | pwd | mx5p | medtpk |
|---|---|---|---|---|---|---|---|---|
| van Dijk | | | | | | | | |
| RMSE | A | 19 | 1.48 (0.40) | 1.53 (0.35) | 0.58 (0.20) | 0.81 (0.31) | 2.96 (0.81) | 0.51 (0.07) |
| | B | 10 | 1.74 (0.56) | 1.55 (0.50) | 0.58 (0.32) | 0.75 (0.21) | 2.97 (0.71) | 0.55 (0.04) |
| | C | 7 | 1.14 (0.66) | 1.14 (0.55) | 0.84 (0.17) | 1.22 (0.62) | 2.71 (1.06) | 0.54 (0.08) |
| KGE | A | 56 | 2.05 (1.44) | 2.43 (0.55) | 0.39 (0.23) | 0.78 (0.37) | 1.66 (0.95) | 0.53 (0.05) |
| | B | 57 | 1.04 (0.20) | 1.34 (0.51) | 0.68 (0.24) | 1.25 (0.28) | 2.71 (1.20) | 0.54 (0.08) |
| | C | 47 | 1.29 (0.68) | 1.27 (0.64) | 0.78 (0.33) | 0.69 (0.39) | 2.06 (1.42) | 0.54 (0.08) |
| Local function | | | | | | | | |
| RMSE | A | 26 | 1.38 (0.36) | 1.51 (0.34) | 0.60 (0.21) | 0.84 (0.28) | 2.77 (0.87) | 0.54 (0.06) |
| | B | 11 | 1.35 (0.24) | 2.00 (0.86) | 0.72 (0.14) | 0.76 (0.25) | 2.24 (0.95) | 0.52 (0.04) |
| | C | 8 | 1.16 (0.34) | 1.32 (0.73) | 0.68 (0.24) | 1.28 (0.55) | 2.80 (0.91) | 0.50 (0.10) |
| KGE | A | 54 | 2.34 (1.29) | 2.18 (0.82) | 0.43 (0.26) | 0.73 (0.47) | 2.37 (1.15) | 0.55 (0.07) |
| | B | 28 | 0.99 (0.21) | 1.57 (0.87) | 0.65 (0.28) | 1.25 (0.28) | 2.46 (1.46) | 0.52 (0.07) |
| | C | 45 | 1.45 (0.67) | 1.58 (0.35) | 0.85 (0.29) | 0.56 (0.11) | 2.45 (1.26) | 0.52 (0.08) |

context of this study i.e. $EI_{30}$ estimation in the present geographical context and are not transferable to other sites. For any other site a re-assessment of the same manner would be necessary, potentially with an even higher number of model runs as the high errors of the top performing parameter sets suggest. As the better alternative to manipulating input data should be to either improve the CLIGEN model itself to match local requirements or to find out about generally valid ways to improve input statistics we want to discuss two suggestions coming from additional observations during the study.

The virtual best parameter values for *meanp*, *mx5p*, *medtpk* and $P(W)$ sum up to the following: The model performs best in reproducing local $EI_{30}$ and R-factors if precipitation amounts and maximum intensities of symmetrical precipitation patterns are higher at a lower number of precipitation events than observed in pluviograph data. Taking an example from Table 2 that would mean at site A to increase the input parameter *meanp* by the factor 1.48, a substantially lower combined transition probability of $P(W) = 0.49$ instead of $P(W) = 0.87$, and a substantial increase in *mx5p* by the factor 2.96. These findings are in contrast to local precipitation regimes where extensive rainfall events with low intensities are more common. But comparing the distribution of storm durations from observed data and CLIGEN output of unaltered runs the changes make sense. In observations > 30% of storms are longer than 18 h. Furthermore, examining single storms, the remaining shorter storms dock on to the long storms and form aforementioned multi-day rain storms. This situation is to some extent preserved in unaltered CLIGEN runs as the vast majority of storms tend to durations of close to 24 h, i.e. also leading to multi-day events. Nevertheless, the low peak intensities of those storms and the resulting form of the double exponential function with low average intensities yield low erosivities during most of the event. If this observation should be cause to a change in model representation of long events with low intensities should be object to further studies. Another explanation to this could be related to our second suggestion. It is widely known that the storm representation with the double exponential function lacks the ability to represent "peakiness" of a storm by reducing it to an event with one peak. We suspect the implications to this to be rather important to the findings in this study. Recorded storms with long durations have several peaks with similar intensities, even on a daily scale. Additionally, peaks are often less pronounced with intensities only slightly above average precipitation. The recommended standard parametrization procedure lets us automatically pick the single highest peak. As a consequence precipitation sums, intensity patterns, and the according rain erosivities of the recorded storms differ from resulting modeled patterns. The calibration functions we developed in this study should actually correct this bias but do not seem to be sufficient. We hence suggest that further research could focus either on expanding the model's representation of internal storm patterns or on finding empirical parameters to incorporate the effects of multiple peaks.

Again, these observations and suggestions should in the first place be considered valid for the context of $EI_{30}$ estimations in the present geographical situation. Whether these issues also appear when CLIGEN is used in its original context together with WEPP in the region of the study needs further evaluation.

Even if our sites are located close to each other at approximately the same elevation ASL R-factors differ clearly with a decrease from station A to C. Besides the strong variation in topography along that short transect this decrease also occurs along the transects' orientation from NE to SW implying a decrease in precipitation quantities or intensities along that path. Still, the RSA showed that model sensitivity to parameter variation is only slightly influenced by erosivity levels and practically not site specific. There is a slight trend towards lower sensitivities at station A, where highest erosivities occur, for *sdevp* with RMSE and *meanp* for KGE, indicating a softening effect of high erosivity on model sensitivity.

In this study RMSE more represents model quality for monthly $EI_{30}$ performance and KGE more represents daily $EI_{30}$ performance of the model approach. So, the here depicted higher sensitivities for RMSE than for KGE mean higher model sensitivities when calculating monthly $EI_{30}$ than when calculating daily $EI_{30}$. This is particularly important as the aim of the method is to provide real R-factors, which are defined as mean annual sums of event based, meaning daily based in CLIGEN, $EI_{30}$. Low parameter sensitivities to daily values add some uncertainty to implementation of future climates, since the effect of manipulation becomes more diffuse. Whether these lower sensitivities are a consequence of the nature of the goodness of fit parameter KGE and its components was not part of this study and would need further investigation of the single components of KGE, as discussed in Gupta et al. (2009).

The sensitivities of the model towards manipulation of *meanp*, *mx5p* and the transition probabilities are most important when implementing different future climate scenarios. For instance, a scenario often discussed is a rise in the magnitude of extreme events. Both a rise in daily precipitation, represented by *meanp*, or in peak precipitation intensity, represented by *mx5p*, would be possible means to put this into effect. To both parameters the model is less sensitive than to the transition probabilities. Hence by modifying only one of the two parameters or by sophisticated balancing changes in both parameters it will be possible to keep control over changes in model output. Another climate change scenario discussed is a mere change in numbers of wet days. Putting this into effect would mean manipulation of the transition probabilities, to which the model is most sensitive in a very narrow parameter range. Also, as mentioned above, the occurrence probability for a wet day, $P(W)$, is dependent on both transition probabilities, meaning that a change in one transition probability would lead to a change in the entire frequency of precipitation. As a consequence it would be necessary to analyze parameter correlations prior to manipulation. Any mix of climate change scenarios, as for example a rise of both wet days as well as precipitation magnitude, would require appropriate levels of sophistication or other methods. One measure could be to calibrate model input parameters to make output meet a desired number of wet days with desired precipitation amounts.

Even if we were able to shed some light on parameter sensitivities and the importance of parameter correlations it is necessary to further validate these with measured data. A possible approach to this would be further research of the kind of Yu (2005), where parameter linearities and correlations were evaluated by re-modeling past climatic change in Australia, given that adequate data is available.

A problem left aside in this study is the representation of seasonality. Each variation factor of an input parameter was applied the same to all twelve monthly values of this parameter. In the first place this was done to reduce the already immense computing capacities needed and to facilitate visualization of parameter variation and results. In the second place seasonality is moderate in the studied region, with slightly higher mean precipitation in the winter months countered by slightly higher precipitation intensities in the summer months. Since one common assumption to climate change proposes that future precipitation changes might predominantly occur in the winter months, it might become crucial to asses possibly different monthly parameter sensitivities in future studies.

## 6. Conclusions

Main focus of this study was to assess CLIGEN application as part of erosion prediction concepts in Central Europe. We presented a framework to analyze model sensitivities by manipulating CLIGEN input data. We derived erosivity indices from CLIGEN output, as presented in Yu (2002), and found a workaround to make the model reproduce rain erosivity for the region of the study. As a general conclusion we can state that CLIGEN performs best in reproducing local rain erosivity when precipitation amounts and maximum intensities of symmetrical precipitation patterns are altered to higher values at a lower number of precipitation events than observed. Referring to the questions we posed

in the beginning we furthermore come to the following conclusions: (1) Unaltered CLIGEN is not suitable to model climatic conditions and erosivity indices in the Northern Black Forest. R-factors from model runs with non-manipulated input data result in about one third of observed R-factors. By empirically adjusting input data model output can be significantly improved (3). The obtained parameters tend to a modeled precipitation regime where precipitation amounts and maximum intensities are higher at a lower number of precipitation events. These findings stand in contrast to known precipitation regimes in this region but remained consistent throughout study sites. Manipulations of CLIGEN input data, even if tight constraints are set to key statistics like annual precipitation, deteriorate observations and are generally problematic. The obtained parameter sets can only be deemed a workaround to make CLIGEN produce better estimates of rain erosivity and to explore the functionality of the model under different climatic conditions than developed in. To meet the desire to benefit from the advantages of CLIGEN and WEPP it is necessary to further research into possibilities to incorporate local weather characteristics into the model.

CLIGEN is very sensitive to manipulation of all of the input parameters affecting precipitation amount and frequency plus the parameter for maximum peak precipitation (4). These parameters are of particular importance when implementing future climate scenarios with a rise in precipitation occurrence, sums or intensity. The more complex a projected climate change scenario gets, the more of these parameters are involved, making it increasingly more difficult to estimate the effect of manipulation of one parameter on model output. Hence it is crucial to further evaluate with historical data how a parameter needs to be manipulated to put a certain projected or desired change into effect.

We can also conclude that model performance and parameter uncertainties did not benefit much from a local kinetic energy function and differences in model errors and sensitivities compared to a universal function remain negligible (2). As a side note we want to emphasize that even with limited reliability on our local function, due to a short field campaign and few data points used in establishing the function, it became obvious that the kinetic energy function from (R)USLE and the one presented by van Dijk et al. (2002) deliver substantially higher values for rain erosivity in our region than the local function. For field campaigns in future studies it would be desirable to also monitor rain kinetic energy with appropriate equipment such as laser disdrometers to verify existing estimates of R-factors derived with common functions in Germany.

## Acknowledgements

The project was funded by the Landesgraduiertendförderung Baden-Württemberg (LGFG, state graduate funding) and the Gesellschaft zur Förderung der forst- und holzwirtschaftlichen Forschung an der Universität Freiburg e.V. (GFH). Study sites were chosen in cooperation with the state's forest authorities of Baden-Württemberg (ForstBW) to represent an area where standard infrastructure measures for logging operations in steep terrain prone to erosion occur. Data sets were provided courtesy of Deutscher Wetterdienst (DWD, German Meteorological Service) as part of their cooperation program with research and education.

Our gratitude to Prof. Bofu Yu for his correspondence helping us to solve the math behind the double exponential function.

Please contact the corresponding author for original and altered CLIGEN parameter files.

## References

Al-Mukhtar, M., Dunger, V., Merkel, B., 2014. Evaluation of the climate generator model CLIGEN for rainfall data simulation in Bautzen catchment area, Germany. Hydorol. Res. 45 (4–5), 615–630.

Arnold, J.G., Williams, J.R., 1989. Stochastic generation of internal storm structure. Trans. ASAE 32 (1), 161–166.

Arnold, J.G., Williams, J.R., Nicks, A.D., Sammons, N.B., 1990. SWRRB, A Basin Scale Simulation for Soil and Water Resources Management. Texas A&M Press, College Station, TX (142 pp).

Blanchard, D.C., 1953. Raindrop size distributions in Hawaiian rains. J. Meteorol. 10, 457–473.

Borelli, P., Panagos, P., Langhammer, J., Apostol, B., Schütt, B., 2016. Assessment of the cover changes and the soil loss potential in European forestland: first approach to derive indicators to capture the ecological impacts in soil-related forest ecosystems. Ecol. Indic. 60, 1208–1220.

Brazier, R.E., Beven, K.J., Anthony, S.G., Rowan, J.S., 2001. Implications of model uncertainty for the mapping of hillslope-scale soil erosion predictions. Earth Surf. Process. Landf. 26, 1333–1352.

Brown, L.C., Foster, G.R., 1987. Storm erosivity using idealized intensity distributions. Trans. ASAE 30, 379–386.

Chaves, H.M.L., Nearing, M.A., 1991. Uncertainty analysis of the WEPP soil erosion model. Trans. ASAE 34, 2437–2444.

Chu, S.T., 1978. Infiltration during an unsteady rain. Water Resour. Res. 14 (3), 461–466.

De Maria, I.C., Chaves, M.O., Ranieri, S.B.L., Sparovek, G., Senelhas, P.C., 2001. Avaliação do modelo CLIGEN na geração de dados climáticos para o modelo de predição de erosão WEPP. In: XIII Reunião Brasileria de Manejo e Conservação do Solo e da Água. Sociedade Brasileira de Ciência do Solo, Ilhéus, Bahia (6-11 de agosto de 2001).

Elliot, W.J., Scheele, D.L., Hall, D.E., 2000. The Forest Service WEPP Interfaces. ASAE Annual International Meeting 2000.

Fan, J.C., Yang, C.H., Liu, C.H., Huan, H.Y., 2013. Assessment and validation of CLIGEN-simulated rainfall data for Northern Taiwan. Paddy Water Environ. 11, 161–173.

Favis-Mortlock, D.T., 1994. Use and Abuse of Soil Erosion Models in Southern England. Ph.D. Thesis. University of Brighton, UK.

Favis-Mortlock, D.T., Boardman, J., 1995. Nonlinear responses of soil erosion to climate change: a modelling study on the UK South Downs. Catena 25, 365–387.

Favis-Mortlock, D.T., Guerra, A.J.T., 1999. The implications of general circulation model estimates of rainfall for future erosion: a case study from Brazil. Catena 37, 329–354.

Favis-Mortlock, D.T., Savabi, M.R., 1996. Shifts in rates and spatial distributions of soil erosion and deposition under climate change. In: Anderson, M.G., Brooks, S.M. (Eds.), Advances in Hillslope Processes. Wiley, Chichester, pp. 529–560.

Flanagan, D.C., Nearing, M.A. (Eds.), 1995. USDA-Water Erosion Prediction Project: Hillslope Profile and Watershed Model Documentation. NSERL Report No. 10. USDA-ARS National Soil Erosion Research Lab, West Lafayette, IN.

Freer, J., Beven, K.J., Ambroise, B., 1996. Bayesian estimation of uncertainty in runoff prediction and the value of data: an application of the GLUE approach. Water Resour. Res. 32, 2161–2173.

Gauer, J., Aldinger, E. (Eds.), 2005. Waldökologische Naturräume Deutschlands – Forstliche Wuchsgebiete und Wuchsbezirke – mit Karte 1:1.000.000. Mitteilunges des Vereins für forstliche Standortskunde und Forstpflanzenzüchtung 43, 324 pages, Freiburg.

Grace III, J.M., 2003. Minimizing the impacts of the forest road system. In: Proceedings of the Conference 34 International Erosion Control Association, Nashville, pp. 301–310.

Gupta, H.V., Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. J. Hydrol. 377, 80–91.

Hinkle, S.E., Heerman, D.F., Blue, M.C., 1987. Falling water drops at 1570 m elevation. Trans. ASAE 30, 94–100.

Hornberger, G.M., Spear, R.C., 1981. An approach to the preliminary analysis of environmental systems. J. Environ. Manag. 12, 7–12.

Kim, M.K., Flanagan, D.C., Frankenberger, J.R., Meyer, C.R., 2009. Impact of precipitation changes on runoff and soil erosion in Korea using CLIGEN and WEPP. J. Soil Water Conserv. 64 (2), 154–162.

Kinnell, P.I.A., 1980. Rainfall intensity-kinetic energy relationships for soil loss prediction. Soil Sci. Soc. Am. Proc. 45, 153–155.

KLIWA, 2008. Klimawandel in Süddeutschland - Veränderung der Kenngrößen Lufttemperatur, Niederschlag und Hochwasserabfluss, Klimamonitoring im Rahmen des Kooperationsvorhabens KLIWA. In: KLIWA Report on Monitoring 2008, . http://www.kliwa.de (29.06.2010).

Kruse, K. (Ed.), 2016. Bodenatlas Deutschland – Böden in thematischen Karten. Bundesanstalt für Geowissenschaften und Rohstoffe (BGR, Federal Institue for Geosciences and Natural Ressources), Hannover (106 pp. ISBN 978-3-510-96855-8).

Laws, J.O., Parsons, D.A., 1943. The relation of raindrop size to intensity. Trans. Am. Geophys. Union 26, 452–460.

Löffler-Mang, M., Joss, J., 2000. An optical disdrometer for measuring size and velocity of hydrometeors. J. Atmos. Ocean. Technol. 17, 130–139.

McIsaac, G.F., 1990. Apparent geographic and atmospheric influences on raindrop sizes and rainfall kinetic energy. J. Soil Water Conserv. 45, 663–666.

Mein, R.G., Larson, C.L., 1973. Modeling infiltration during a steady rain. Water Resour. Res. 9 (2), 384–394.

Meyer, C.R., Renschler, C., Vining, R.C., 2002. Implementing quality control techniques for random number generators to improve stochastic weather generators: the CLIGEN experience. In: Conference of Applied Climatology 13, May 12–16, 2002.

Meyer, C.R., Renschler, C.S., Vining, R.C., 2008. Implementing quality control on a random number stream to improve a stochastic weather generator. Hydrol. Process. 22 (8), 1069–1079.

Morgan, R.P.C., 2005. Soil Erosion and Conservation, 3rd edition. Blackwell Publishing, Oxford, UK.

Nearing, M.A., Dear-Ascough, L., Laflen, J.M., 1990. Sensitivity analysis of the WEPP hillslope erosion model. Trans. ASAE 33, 839–849.

Nicks, A.D., Lane, L.J., 1989. Weather generator. Chapter 2 in USDA – Water Erosion

Prediction Project: hillslope PROFILE version. In: Lane, L.J., Nearing, M.A. (Eds.), NSERL Report No. 2. pp. 2.1–2.22 (West Lafayette, Ind.).
Nicks, A.D., Lane, L.J., Gander, G.A., 1995. Weather generator. Chapter 2 in USDA – Water Erosion Prediction Project: hillslope profile and watershed model documentation. In: Flanagan, D.C., Nearing, M.A. (Eds.), NSERL Report No. 10. USDA-ARS National Soil Erosion Search Laboratory, West Lafayette, IN.
Panagos, P., Borrelli, P., Spinoni, J., Ballabio, C., Meusburger, K., Beguería, S., Klik, A., Michaelides, S., Petan, S., Hrabalíková, M., Olsen, P., Aalto, J., Lakatos, M., Rymszewicz, A., Dumitrescu, A., Tadic, M.P., Diodato, N., Kostalova, J., Rousseva, S., Banasik, K., Alewell, C., 2016. Monthly rainfall erosivity: conversion factors for different time resolutions and regional assessments. Water 8 (4) (No 119).
Pruski, F.F., Nearing, M.A., 2002. Runoff and soil loss responses to changes in precipitation: a computer simulation study. J. Soil Water Conserv. 57, 7–16.
Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K., Yoder, D.C., 1997. Predicting soil erosion by water: a guide to conservation planning with the revised universal soil loss equation (RUSLE). In: Agriculture Handbook No. 703. US Department of Agriculture (Coordinators; 404 pp).
Sauerborn, P., 1994. Die Erosion der Niederschläge in Europa – Erste Ergebnisse einer einheitlichen Gefahrenstufenkarte: Deutschland, Frankreich, Österreich, Mitteilung der Deutschen Bodenkundlichen Gesellschaft. 79. pp. 423–426.
Savabi, M.R., Williams, J.R., 1995. Water balance and percolation, chapter 5 in USDA – Water Erosion Prediction Project: hillslope profile and watershed model documentation. In: Flanagan, D.C., Nearing, M.A. (Eds.), NSERL Report No. 10. USDA-ARS National Soil Erosion Search Laboratory, West Lafayette, IN.
Schmid, T., 2004. The influence of microrelief on erodibility and the change of precipitation erosivity by the tree-canopy passage evaluated exemplarily for a crawler-harvester operation on a steep-slope site. (In German language) Freiburger Bodenkundliche Abhandlungen 41, 129 pages, Freiburg, Germany.
Spear, R.C., Hornberger, G.M., 1980. Eutrophication in peel inlet-II. Identification of critical uncertainties via generalized sensitivity analysis. Water Resour. Res. 14, 43–49.
Stone, J.J., Lane, L.J., Shirley, E.D., Hernandez, M., 1995. Hillslope surface hydrology, chapter 4 in USDA – Water Erosion Prediction Project: hillslope profile and watershed model documentation. In: Flanagan, D.C., Nearing, M.A. (Eds.), NSERL Report No. 10. USDA-ARS National Soil Erosion Search Laboratory, West Lafayette, IN.
van Dijk, A.I.J.M., Bruijnzeel, L.A., Rosewell, C.J., 2002. Rainfall intensity-kinetic energy relationships: a critical literature review. J. Hydrol. 261, 1–23.
Wagener, T., Boyle, D.P., Less, M.J., Wheater, H.S., Gupta, H.V., Sorooshian, S., 2001. A framework for development and application of hydrological models. Hydrol. Earth Sci. 5 (1), 13–26.
Williams, J.R., Jones, C.A., Dyke, P.T., 1984. A model approach to determining the relationship between erosion and soil productivity. Trans. ASAE 27, 129–144.
Wischmeier, W.H., Smith, D.D., 1978. Predicting rainfall erosion losses: a guide to conservation planning. In: Agriculture Handbook No. 537. USDA/Science and Education Administration, US. Govt. Printing Office, Washington, DC (58 pages).
Yu, B., 2002. Using CLIGEN to generate RUSLE climate inputs. Trans. ASAE 45 (4), 993–1001.
Yu, B., 2005. Adjustment of CLIGEN parameters to generate precipitation change scenarios in southeastern Australia. Catena 61, 196–209.
Yu, B., Rosewell, C.J., 2001. Validation of WEPP runoff and soil loss prediction at Gunnedah, NSW, Australia. Aust. J. Soil Res. 39, 1131–1145.
Yu, B., Ciesiolka, C.A.A., Rose, C.W., Coughlan, K.J., 2000. A validation test of WEPP to predict runoff and soil loss from a pineapple farm on a sandy soil in subtropical Queensland, Australia. Aust. J. Soil Res. 38, 537–554.
Zhang, X.C., Garbrecht, J.D., 2003. Evaluation of CLIGEN precipitation parameters and their implication on WEPP runoff and erosion prediction. Trans. ASAE 46 (2), 311–320.